

Estimating Social Preferences From Dictator Game Data

估計社會偏好：以獨裁分配實驗結果為例

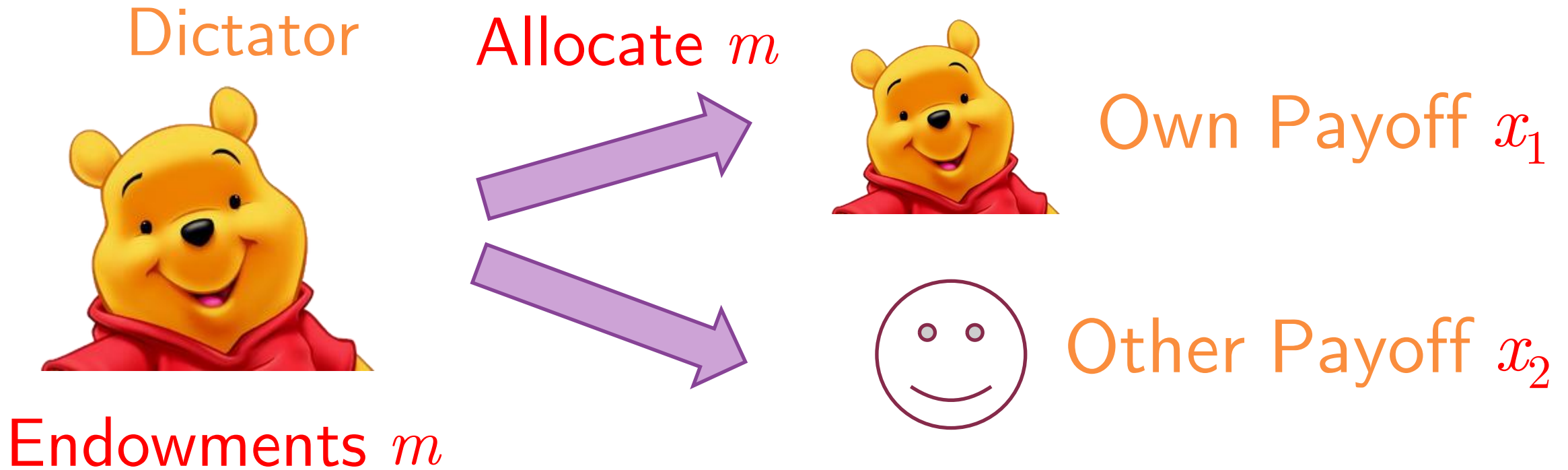
Joseph Tao-yi Wang (王道一)
Experimentetrics Lecture 5 (實驗計量第五講)

Part I: Dictator Game with Prices

第一部分：不同價格下的獨裁分配

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The Dictator Game



- ▶ One Subject Chooses Allocation for Both
 - ▶ The Dictator

The Dictator

Dictator



Payoff x_1

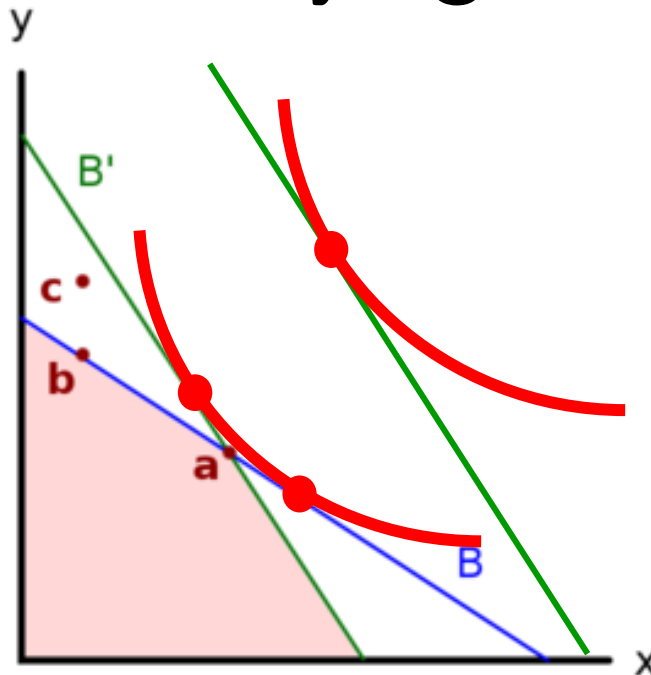
Payoff x_2

Endowment

- ▶ One Subject
- ▶ The Dictator

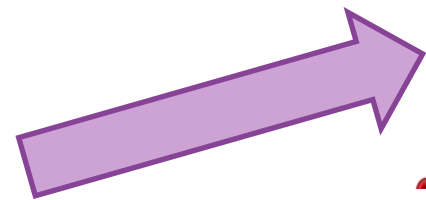
Involving Prices: Andreoni and Miller (2002)

- ▶ Alter Endowment m , Prices of Keeping p_1 and Giving p_2
- ▶ To test if choice data x_1 and x_2 is Rationalizable
- ▶ If yes, can estimate underlying utility function
- ▶ Satisfy GARP?

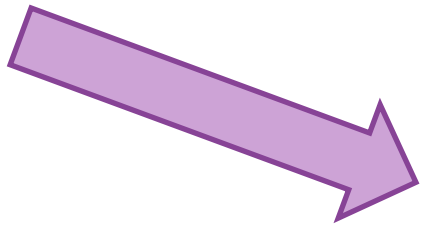


The Dictator Game with Prices

Dictator Allocate m



Directed to Self p_1x_1



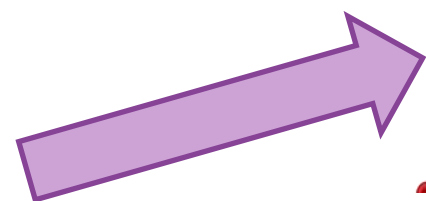
Directed to Other p_2x_2

Endowments $m = p_1x_1 + p_2x_2$

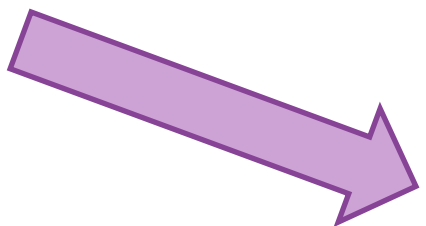
- ▶ One Subject Chooses Allocation for Both
 - ▶ The Dictator

The Dictator Game with $(p_1, p_2) = (1/3, 1)$

Dictator Allocate 40



Directed to Self $(1/3)x_1$



Directed to Other $1x_2$

Endowments $m = 40$

▶ If $1x_2 = 30$, $(1/3)x_1 + 1x_2 = 40$

▶ Then $(1/3)x_1 = 40 - 30 = 10$

So, $x_1 = 30!$

Data of Andreoni and Miller (2002)

- ▶ Choose $p_1 x_1$ Directed to Self
 - ▶ Amount Received by Self x_1 (and Price of Keeping p_1)
- ▶ Choose $p_2 x_2$ Directed to Other
 - ▶ Amount Received by Other: x_2 (and Price of Giving p_2)
- ▶ Subject to Budget Constraint: $p_1 x_1 + p_2 x_2 \leq m$
 - ▶ Since BC binds, choose only $p_2 x_2$ and $p_1 x_1 = m - p_2 x_2$
- ▶ Define Budget Shares $w_1 = \frac{p_1 x_1}{m}$, $w_2 = \frac{p_2 x_2}{m}$
 - ▶ N=176: `garp.dta`

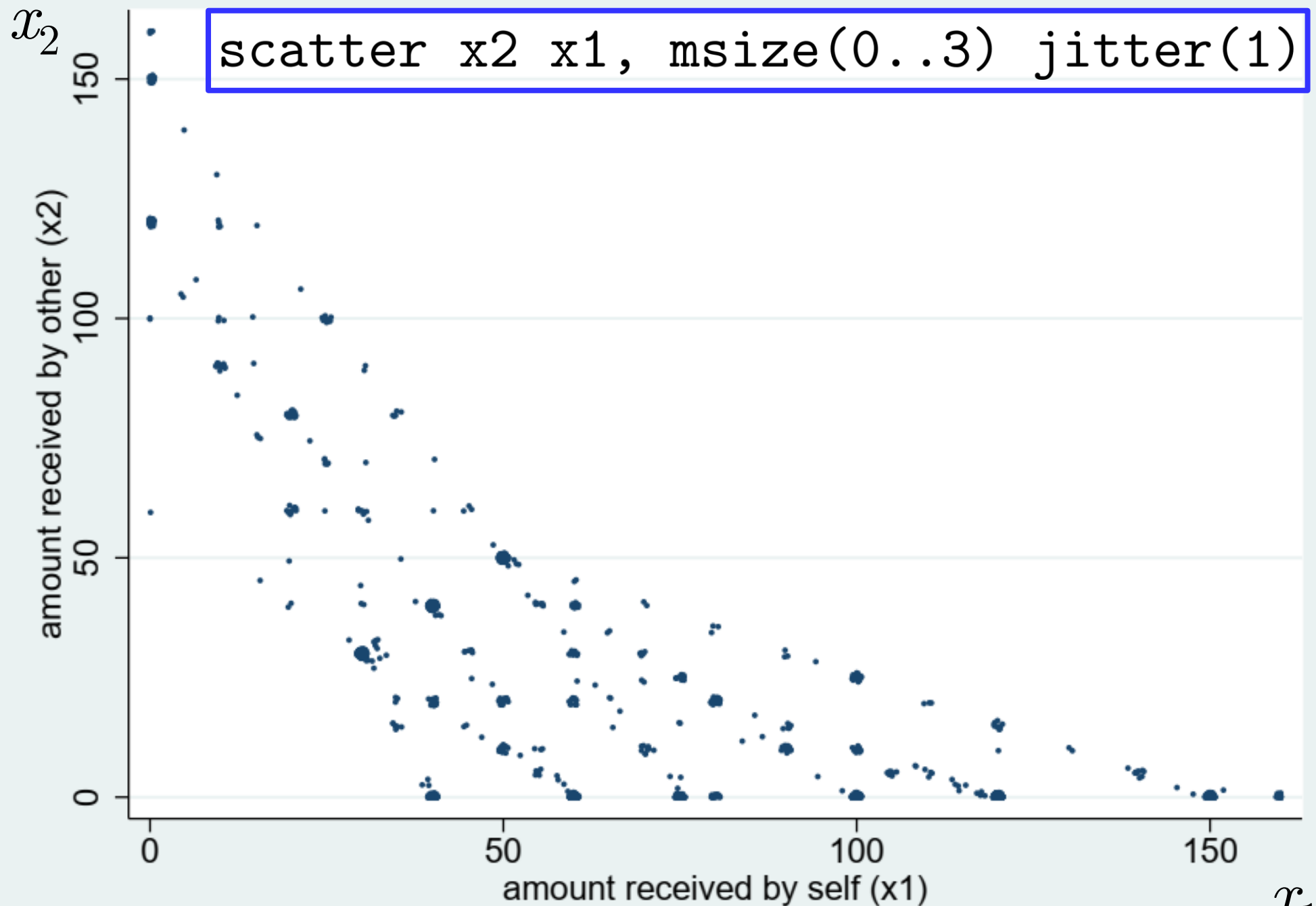
11 Budget Sets Presented in Random Order

Budget	m	p_1	p_2	Observations	Mean amount sent to other
1	40	0.33	1	176	8.02
2	40	1	0.33	176	12.81
3	60	0.5	1	176	12.67
4	60	1	0.5	176	19.40
5	75	0.5	1	176	15.51
6	75	1	0.5	176	22.68
7	60	1	1	176	14.55 / 60 = 24%
8	100	1	1	176	23.03 / 100 = 23%
9	80	1	1	34	13.5 / 80 = 17%
10	40	0.25	1	34	3.41
11	40	1	0.25	34	14.76

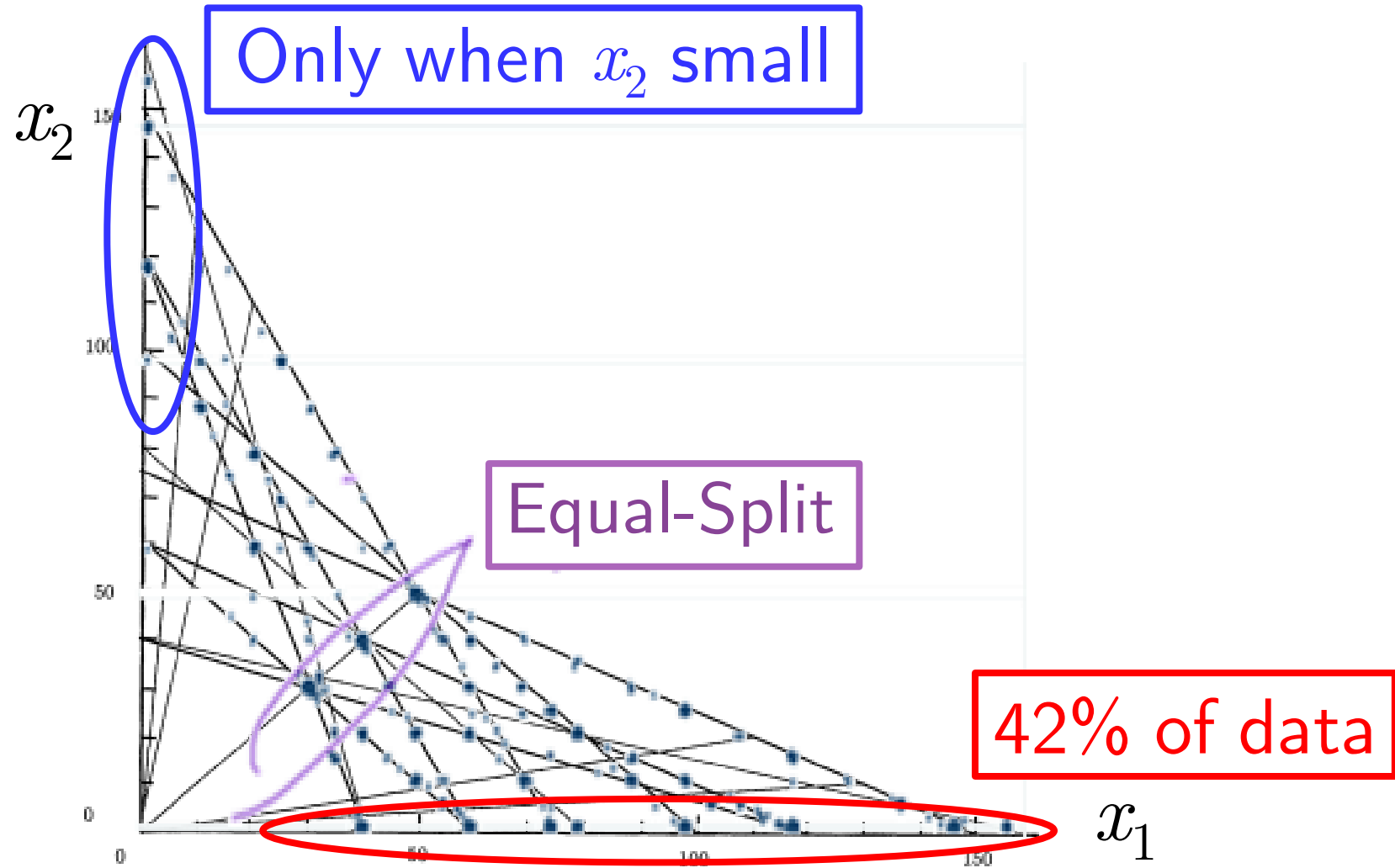
Give 17-24% in standard, (1,1)-dictator games consistent with Camerer (2003)

Property 1:

▶ STATA
Results:

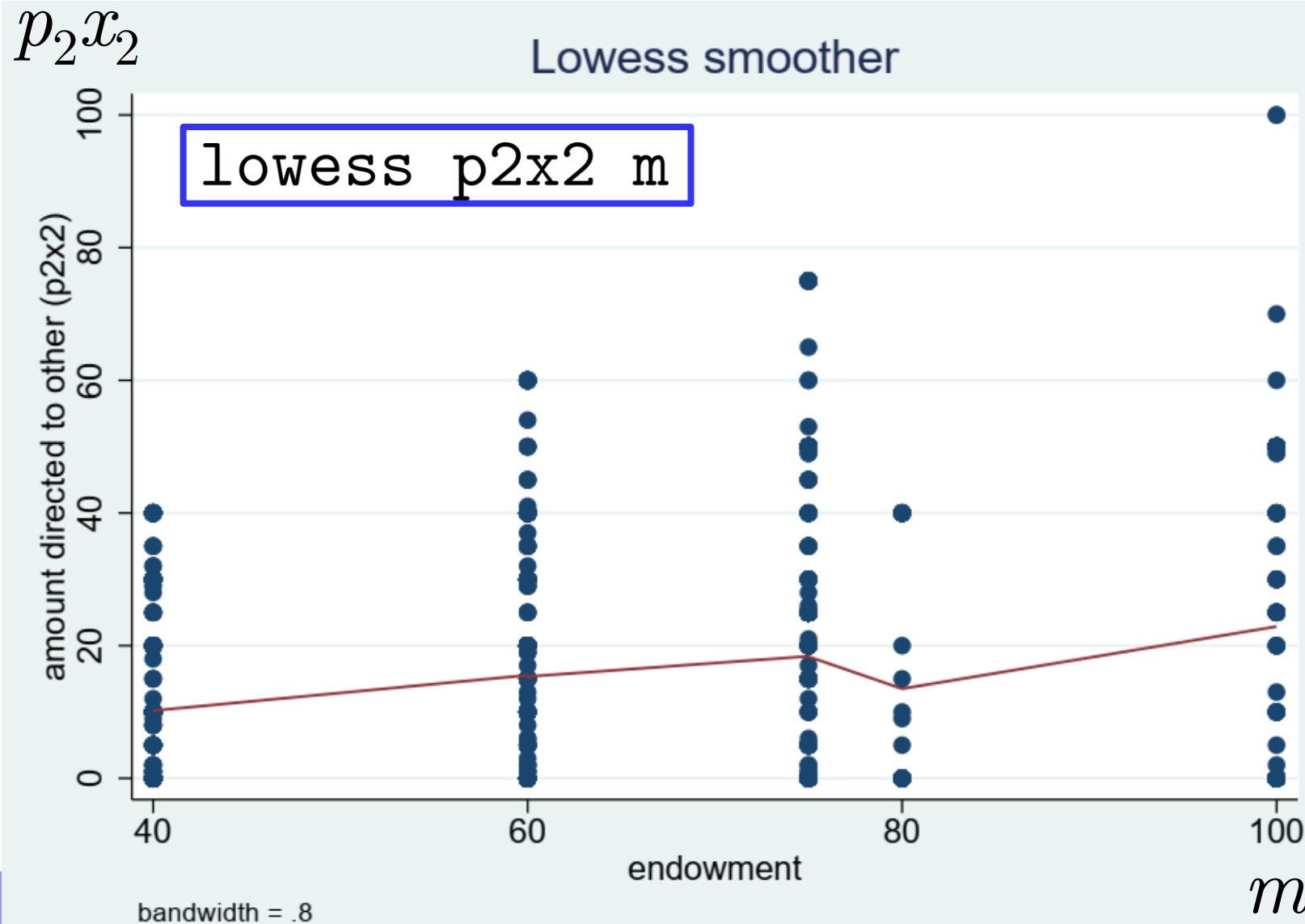


Property 1: Bias Toward Giving-to-Self



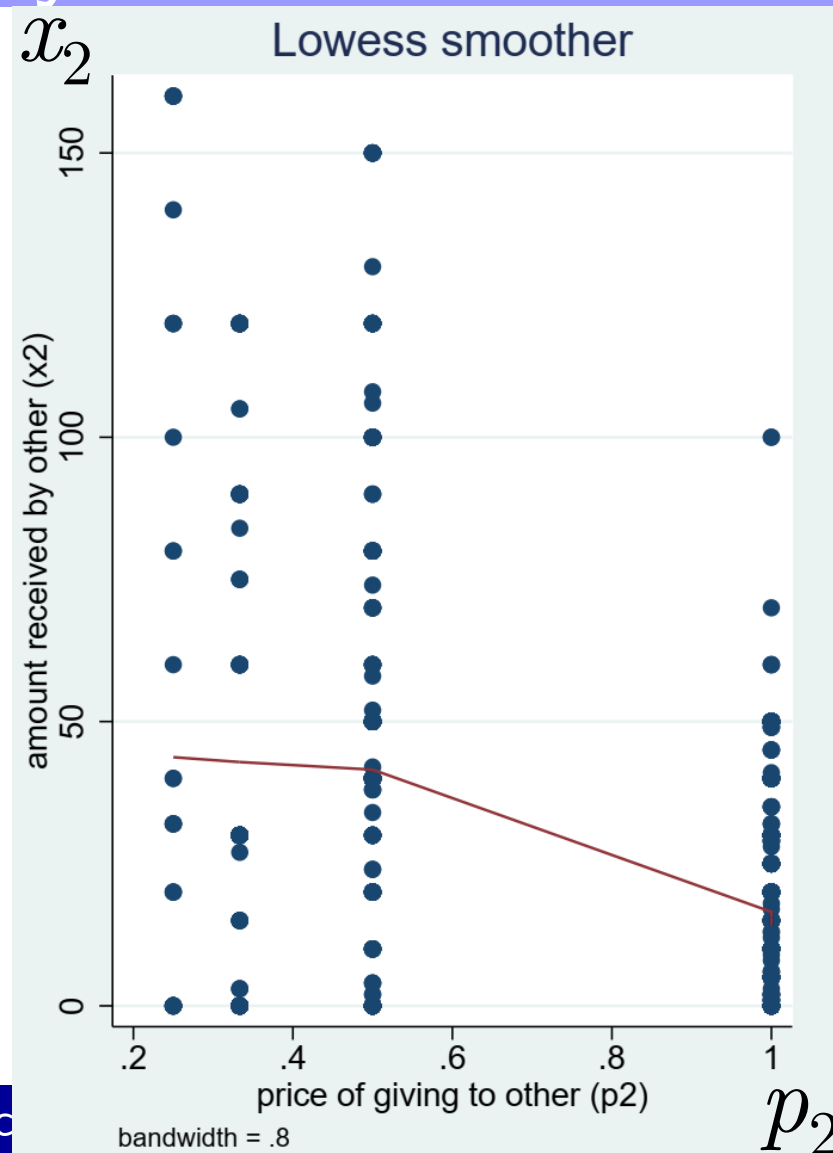
Property 2: Giving (x_2) is a Normal Good

► STATA
Results:



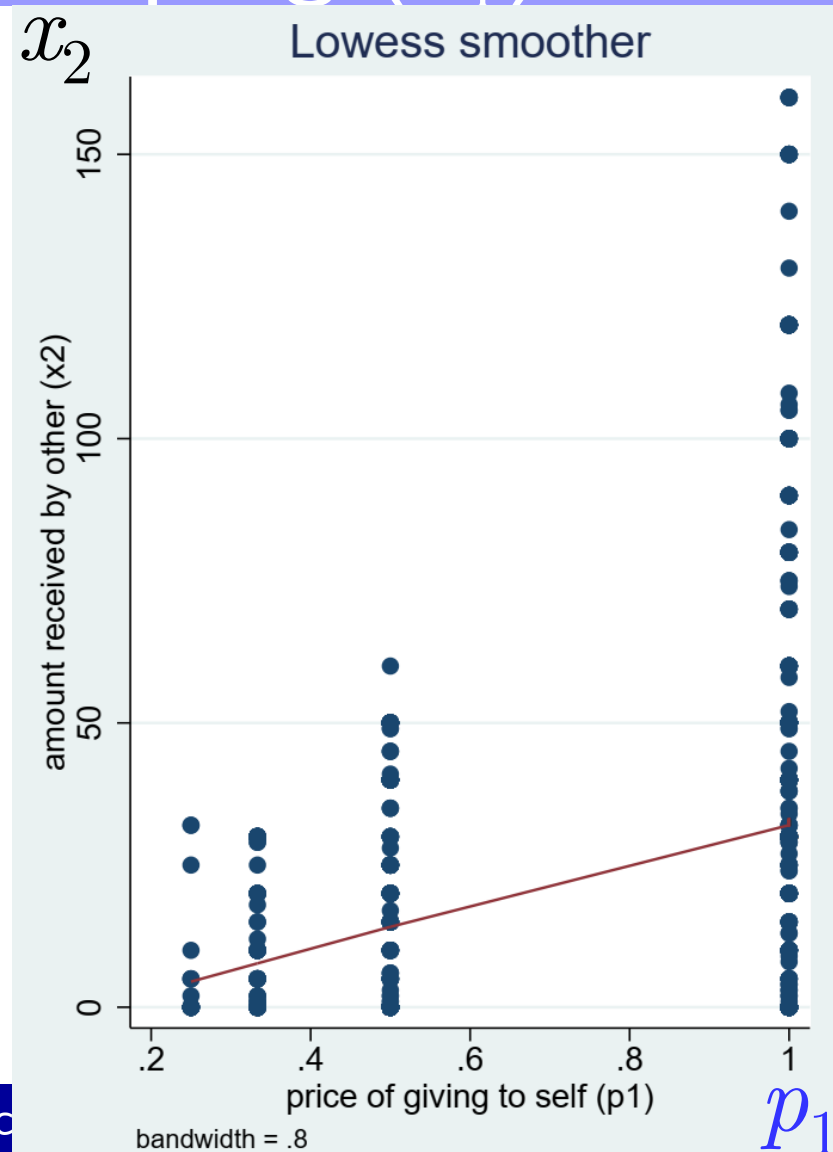
Property 3: Giving (x_2) Obeys Law of Demand

► STATA `lowess x2 p2`
Results:



Property 4: Giving (x_2) & Keeping (x_1) are Substitutes

► STATA `lowess x2 p1`
Results:



Property 3 and 4: Linear Regression

▶ STATA regress x2 p2 p1, vce(cluster i)

Results:

Linear regression

Number of obs = 1510
F(2, 175) = 61.20
Prob > F = 0.0000
R-squared = 0.1847
Root MSE = 28.661

Giving Obeys Law of Demand ($t = -7.90$)

Giving and Keeping are Substitutes ($t = 8.70$)

(Std. Err. adjusted for 176 clusters in i)

		Robust				
x2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
p2	-39.00726	4.934956	-7.90	0.000	-48.74695	-29.26757
p1	14.47704	1.664276	8.70	0.000	11.1924	17.76167
_cons	43.95138	4.663821	9.42	0.000	34.74681	53.15596

Property 2: Adding Income to the Linear Regression

▶ STATA regress x2 p2 p1 m, vce(cluster i)

Results:

Linear regression

p_1 Highly Correlated with m and No Longer Significant (Previously Served as its Proxy)

Giving is a Normal Good ($t = 9.57$): When m Increases by 1, Giving Increases by 0.265

Number of obs = 1510
F(3, 175) = 61.25
Prob > F = 0.0000
R-squared = 0.1976
Root MSE = 28.441

(Std. Err. adjusted for 176 clusters in i)

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2							
p2		-52.12677	5.063235	-10.30	0.000	-62.11964	-42.13391
p1		1.357528	1.783083	0.76	0.447	-2.161587	4.876643
m		.265248	.0277023	9.57	0.000	.2105744	.3199216
_cons		47.92717	4.707122	10.18	0.000	38.63713	57.2172

Tobit Regression: Account for 42% Giving Zero

▶ STATA `tobit x2 p2 p1 m, vce(cluster i) ll(0)`

Results:

```
Tobit regression                               Number of obs   =       1510
                                                F(   3,   1507) =       54.33
                                                Prob > F        =       0.0000
Log pseudolikelihood = -5027.146              Pseudo R2       =       0.0256
```

Stronger Overall Results!

Tobit Coefficient for p_1 (10.81, $t=2.76$) is 8 Times Larger than OLS (1.36, $t = 0.76$)

(Std. Err. adjusted for 176 clusters in i)

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2						
p2	-67.1347	7.049639	-9.52	0.000	-80.96285	-53.30656
p1	10.8052	3.910197	2.76	0.006	3.135191	18.4752
m	.3322818	.0380964	8.72	0.000	.2575541	.4070095
_cons	34.41715	6.122105	5.62	0.000	22.4084	46.4259
/sigma	42.59774	2.46888			37.75494	47.44055

```
Obs. summary:      628 left-censored observations at x2<=0
                   882 uncensored observations
                   0 right-censored observations
```

Random Effect Tobit Regression: Panel Data

▶ STATA `xtset i t`

Results: `xttobit x2 p2 p1 m, ll(0)`

```
Random-effects Tobit regression                Number of obs      =       1510
Group variable: i                            Number of groups   =        176

Random effects u_i ~ Gaussian                Obs per group: min =         8
                                                avg  =         8.6
                                                max  =         11

Integration method: mvaghermite              Integration points =         12

Wald chi2(3)                                 =       605.11
Log likelihood = -4663.2072                   Prob > chi2        =       0.0000
```

	x2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
	p2	-75.14353	4.942489	-15.20	0.000	-84.83063	-65.45643
	p1	9.896787	5.060785	1.96	0.051	-.0221691	19.81574
	m	.3672872	.0639333	5.74	0.000	.2419803	.4925941

Random Eff

▶ STATA Results:

```
Random-effects Tobit regression
Group variable: i

Random effects u_i ~ Gaussian

Integration method: mvaghermite

Log likelihood = -4663.2072

Number of obs = 1510
Number of groups = 176
Obs per group: min = 8
                avg = 8.6
                max = 11

Integration points = 12

Wald chi2(3) = 605.11
Prob > chi2 = 0.0000
```

Even Stronger Results!

Between-Subject Heterogeneity is Large (44.06) and Significant ($t=13.45$)

x2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
p2	-75.14353	4.942489	-15.20	0.000	-84.83063	-65.45643
p1	9.896787	5.060785	1.96	0.051	-.0221691	19.81574
m	.3672872	.0639333	5.74	0.000	.2419803	.4925941
_cons	32.68706	6.512942	5.02	0.000	19.92193	45.4522
/sigma_u	44.0585	3.276081	13.45	0.000	37.6375	50.4795
/sigma_e	28.67666	.7433699	38.58	0.000	27.21968	30.13364
rho	.7024244	.0320737			.6367994	.7620325

Constant Elasticity of Substitution Utility Function

- ▶ Andreoni and Miller (2002) Estimate Social Preference via
- ▶ **CES: Constant Elasticity of Substitution Utility Function**

$$U(x_1, x_2) = [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho}}$$

- ▶ **Selfishness:** $0 \leq \alpha \leq 1$
- ▶ Willingness to Trade Off Equity and Efficiency: $-\infty \leq \rho \leq 1$
- ▶ **Elasticity of Substitution:** $\sigma = \frac{1}{1 - \rho}$
- ▶ Estimate $\hat{\alpha}, \hat{\rho}$ from behavior in Dictator Game

Constant Elasticity of Substitution Utility Function

▶ CES Utility Function $U(x_1, x_2) = [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho}}$, $\sigma = \frac{1}{1-\rho}$

1. Perfect Substitutes (**Linear**):

▶ Focus on **Efficiency**: $\sigma \rightarrow \infty, \Rightarrow \rho \rightarrow 1$

$$\Rightarrow U(x_1, x_2) \rightarrow \alpha x_1 + (1 - \alpha)x_2$$

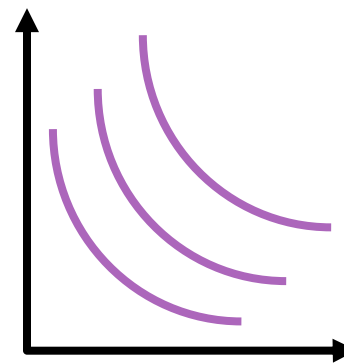
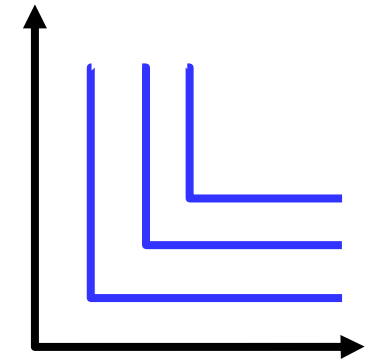
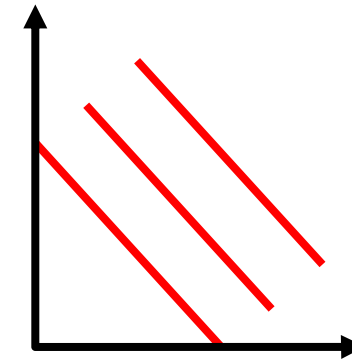
2. Perfect Complements (**Leontief**):

▶ Focus on **Equity**: $\sigma \rightarrow 0, \Rightarrow \rho \rightarrow -\infty$

$$\Rightarrow U(x_1, x_2) \rightarrow \min \{ \alpha x_1, (1 - \alpha)x_2 \}$$

3. Cobb-Douglas: $\sigma \rightarrow 1, \Rightarrow \rho \rightarrow 0$

$$\Rightarrow U(x_1, x_2) \rightarrow x_1^\alpha x_2^{1-\alpha}$$



Demand Function Derived From CES Utility Function

► Consumer Problem with CES Utility Function

$$\max_{x_1, x_2} U(x_1, x_2) = [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho}} \text{ s.t. } p_1 x_1 + p_2 x_2 \leq m$$

$$\mathcal{L} = [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho}} - \lambda (p_1 x_1 + p_2 x_2 - m)$$

$$\text{FOC: } \frac{\partial \mathcal{L}}{\partial x_1} = \frac{1}{\rho} [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho} - 1} \cdot \rho \alpha x_1^{\rho - 1} - \lambda p_1 \leq 0, x_1 \geq 0$$

$$\frac{\partial \mathcal{L}}{\partial x_2} = \frac{1}{\rho} [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho} - 1} \cdot \rho (1 - \alpha) x_2^{\rho - 1} - \lambda p_2 \leq 0, x_2 \geq 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = p_1 x_1 + p_2 x_2 - m \leq 0, \lambda \geq 0$$

Demand Function Derived From CES Utility Function

- ▶ Constraint binds; x_1 and x_2 are positive (increasing U):

$$(1) = \frac{1}{\rho} [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho} - 1} \cdot \rho \alpha x_1^{\rho - 1} = \lambda p_1$$

$$(2) = \frac{1}{\rho} [\alpha x_1^\rho + (1 - \alpha)x_2^\rho]^{\frac{1}{\rho} - 1} \cdot \rho(1 - \alpha)x_2^{\rho - 1} = \lambda p_2$$

$$(3) = p_1 x_1 + p_2 x_2 = m$$

$$\Rightarrow \frac{(2)}{(1)} = \frac{(1 - \alpha)}{\alpha} \left(\frac{x_2}{x_1} \right)^{\rho - 1} = \frac{p_2}{p_1} \Rightarrow \left(\frac{p_2}{p_1} \cdot \frac{\alpha}{1 - \alpha} \right)^{\frac{1}{\rho - 1}} = \frac{x_2}{x_1}$$

Demand Function Derived From CES Utility Function

$$\Rightarrow x_2 = \left(\frac{p_2}{p_1} \cdot \frac{\alpha}{1-\alpha} \right)^{\frac{1}{\rho-1}} \cdot x_1$$
$$(3) = m = p_1 x_1 + p_2 x_2 = x_1 \cdot \left[p_1 + p_2 \left(\frac{p_2}{p_1} \cdot \frac{\alpha}{1-\alpha} \right)^{\frac{1}{\rho-1}} \right]$$

$$\Rightarrow x_1^* = \frac{m}{p_1 + p_2 \left(\frac{p_2}{p_1} \cdot \frac{\alpha}{1-\alpha} \right)^{\frac{1}{\rho-1}}} = \frac{m p_1^{\frac{1}{\rho-1}}}{p_1^{\frac{\rho}{\rho-1}} + p_2^{\frac{\rho}{\rho-1}} \left(\frac{\alpha}{1-\alpha} \right)^{\frac{1}{\rho-1}}}$$

$$\Rightarrow w_1^* = \frac{p_1 x_1^*}{m} = \frac{p_1^{\frac{\rho}{\rho-1}}}{p_1^{\frac{\rho}{\rho-1}} + p_2^{\frac{\rho}{\rho-1}} \left(\frac{\alpha}{1-\alpha} \right)^{\frac{1}{\rho-1}}}, \quad w_2^* = 1 - w_1^*$$

Estimating CES Demand via Non-Linear Least Square

- ▶ Hence, we estimate **Non-Linear Least Square (NLLS)**:

$$w_1 = \frac{p_1^{\frac{\rho}{\rho-1}}}{p_1^{\frac{\rho}{\rho-1}} + p_2^{\frac{\rho}{\rho-1}} \left(\frac{\alpha}{1-\alpha}\right)^{\frac{1}{\rho-1}}} + \epsilon$$

- ▶ For a sample of size n , consisting of w_{1i}, p_{1i}, p_{2i}
- ▶ Find $\hat{\alpha}, \hat{\rho}$ to minimize squared random error:

$$\sum_{i=1}^n \left[w_{1i} - \frac{p_{1i}^{\frac{\rho}{\rho-1}}}{p_{1i}^{\frac{\rho}{\rho-1}} + p_{2i}^{\frac{\rho}{\rho-1}} \left(\frac{\alpha}{1-\alpha}\right)^{\frac{1}{\rho-1}}} \right]^2$$

Estimating CES Demand via Non-Linear Least Square

▶ STATA Command: nl

{rho} and {aa} in {} are to be estimated

```
. nl (w1 = (p1^{rho}/(rho-1))/(p1^{rho}/(rho-1) ///  
> +((aa)/(1-aa))^(1/(rho-1))*(p2^{rho}/(rho-1)))) , ///  
> initial(rho 0.0 aa 0.5) vce(cluster i)
```

Provide Starting Values
for NL Optimization
(Required to Run!)

Cluster-Robust Standard Errors

▶ Applied to Andreoni and Miller (2002) data, we have...

Estimating CES Demand via Non-Linear Least Square

STATA Results:

```
Iteration 0: residual SS = 122.2299
Iteration 1: residual SS = 115.4766
Iteration 2: residual SS = 115.4615
Iteration 3: residual SS = 115.4615
Iteration 4: residual SS = 115.4615
```

Need to Use Delta Method to Recover Elasticity of Substitution

Subjects take about 69.2% for themselves (Relatively Selfish as C.I. > 50%)

```
Nonlinear regression                               Number of obs =      1510
                                                    R-squared          =      0.8804
                                                    Adj R-squared     =      0.8798
                                                    Root MSE         =      .2767056
                                                    Res. dev.        =      403.0932

                                                    (Std. Err. adjusted for 176 clusters in i)
```

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
w1						
/rho	.272248	.0479813	5.67	0.000	.1775515	.3669445
/aa	.6918387	.0150264	46.04	0.000	.6621824	.721495

Estimate Elasticity of Substitution

▶ With $\hat{\rho}$

w1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
/rho	.272248	.0479813	5.67	0.000	.1775515 .3669445
/aa	.6918387	.0150264	46.04	0.000	.6621824 .721495

▶ Can Calculate Elasticity of Substitution:

$$\hat{\sigma} = \frac{1}{1 - \hat{\rho}} = \frac{1}{1 - 0.272248} = 1.37 > 1 \quad \text{Efficiency} > \text{Equality}$$

▶ STATA: `nlcom sigma: 1/(1- _b[rho:_cons])`

(s.e./CI
via Delta
Method)

w1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
sigma	1.374095	.0905952	15.17	0.000	1.196531 1.551658

Part II: Using Discrete Choice Models

第二部分：使用離散選擇模型

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Experimetrics Lecture 5 (實驗計量第五講)

Dictator Game with Discrete Choice

- ▶ Engelmann and Strobel (2004)
- ▶ Ask Subjects to Choose Among Several Allocations
- ▶ To Estimate Utility Function of Own vs. Other Payoffs
- ▶ (As Person 2)
- ▶ Use Discrete Choice Models

Allocation	A	B	C
Person 1	8	6	10
Person 2	8	6	7
Person 3	4	6	7
Total	20	18	24

Various Types of Social Preferences

- ▶ **Selfish** Types: Chooses A to earn \$8
 - ▶ Better than B (\$6) or C (\$7)
- ▶ **Inequity-Averse** Types: Choose B to let all earn \$6
 - ▶ Guilt if A: $\$8 > \4 of Person 3
 - ▶ Envy if C: $\$7 < \10 of Person 1
- ▶ **Efficiency** Types: Choose C to maximize total surplus = \$24
 - ▶ Not Pareto Dominant!

Allocation	A	B	C
Person 1	8	6	10
Dictator	8	6	7
Person 3	4	6	7
Total	20	18	24

Discrete Choice Models

▶ **Efficiency:**

$$EFF_j = \sum_{k=1}^3 x_{jk}$$

x_{jk} = Payoff of Person k
in Allocation j

▶ $EFF_A = 20$; $EFF_B = 18$; $EFF_C = 24$

▶ **Minimax:**

$$MM_j = \min_{k=1,2,3} x_{jk}$$

▶ $MM_A = 4$; $MM_B = 6$; $MM_C = 7$

▶ **Self:**

$$SELF_j = x_{j2}$$

$SELF_A = 8$; $SELF_B = 6$; $SELF_C = 7$

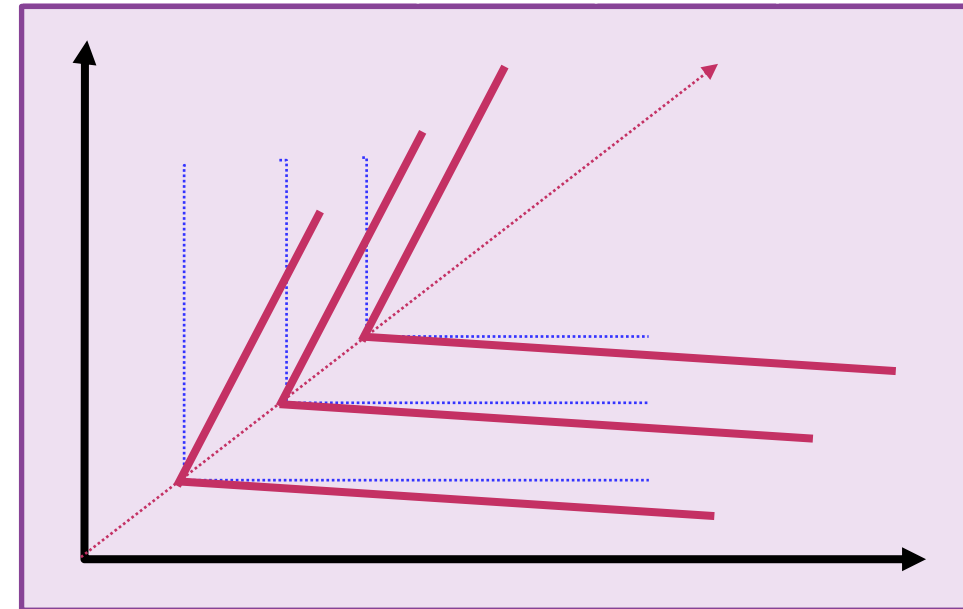
Allocation	A	B	C
Person 1	8	6	10
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Person 3	4	6	7
Total	20	18	24

Discrete Choice Models: Fehr and Schmidt (1999)

- ▶ F-S Utility Function: $(n \text{ Players; } x_i = \text{Person } i \text{ Payoff})$

$$u_i = x_i - \frac{\alpha_i}{n-1} \sum_{k \neq i} \max(x_k - x_i, 0) - \frac{\beta_i}{n-1} \sum_{k \neq i} \max(x_i - x_k, 0)$$

- ▶ **Envy** α_i
 - ▶ Disadvantageous Inequality
- ▶ **Guilt** β_i
 - ▶ Advantageous Inequality
- ▶ Envy greater than Guilt: $\alpha_i > \beta_i$



Discrete Choice Models: Fehr and Schmidt (1999)

$$u_i = x_i - \frac{\alpha_i}{n-1} \sum_{k \neq i} \max(x_k - x_i, 0) - \frac{\beta_i}{n-1} \sum_{k \neq i} \max(x_i - x_k, 0)$$

(n Players;
 $x_i =$ Payoff
of Person i)

▶ Disadvantageous Inequality ($ENVY_j$):

▶ $FSD_A = 0$; $FSD_B = 0$; $FSD_C = -3/2$

$$FSD_j = -\frac{1}{2} \sum_{k \neq j} \max(x_{jk} - x_{j2}, 0)$$

▶ Advantageous Inequality (GLT_j):

▶ $FSA_A = -2$; $FSA_B = 0$; $FSA_C = 0$

$$FSA_j = -\frac{1}{2} \sum_{k \neq j} \max(x_{j2} - x_{jk}, 0)$$

Allocation	A	B	C
Person 1	8	6	10
Dictator	8	6	7
Person 3	4	6	7
Total	20	18	24

Conditional Logit Model (CLM)

- ▶ Simulated Engelmann and Strobel (2004): `ES_sim.dta`
- ▶ $J=3$ rows per subject: `asclogit` (Alternative-Specific CLM)
- ▶ Utility of Subject i for Allocation j is

$$U_{ij} = \alpha_1 FSD_{ij} + \alpha_2 FSA_{ij} + \alpha_3 EFF_{ij} + \alpha_4 MM_{ij} + \epsilon_{ij}$$
$$= \underline{\vec{z}_{ij}' \vec{\alpha}} + \underline{\epsilon_{ij}} \text{ Random Component}$$

Deterministic Component

- ▶ Intercept Not Identified (Does not affect behavior!)

Conditional Logit Model (CLM)

- ▶ $y_{ij} = 1$: Chosen if $U_{ij} = \max(U_{i1}, U_{i2}, \dots, U_{iJ})$
- ▶ $y_{ij} = 0$: Not Chosen otherwise

$$y_{ij} = 1 \Leftrightarrow \vec{z}_{ij}'\vec{\alpha} + \epsilon_{ij} > \vec{z}_{ik}'\vec{\alpha} + \epsilon_{ik}, \quad \forall k \neq j$$
$$\Leftrightarrow \epsilon_{ik} - \epsilon_{ij} < \vec{z}_{ij}'\vec{\alpha} - \vec{z}_{ik}'\vec{\alpha}, \quad \forall k \neq j$$

- ▶ The Conditional Logit Model yields:

$$\Pr(y_{ij} = 1) = \frac{\exp(\vec{z}_{ij}'\vec{\alpha})}{\sum_{k=1}^J \exp(\vec{z}_{ik}'\vec{\alpha})}$$

(aka Gumbel distribution)

- ▶ Maddala (1983): ϵ_{ij} 's iid Type I Extreme Value distribution

Conditional Logit Model (CLM)

- ▶ Assume ϵ_{ij} 's are iid Type I Extreme Value distribution with pdf: $f(\epsilon) = \exp(-\epsilon - \exp(-\epsilon))$, $-\infty < \epsilon < \infty$
- ▶ And cdf: $F(\epsilon) = \exp(-\exp(-\epsilon))$, $-\infty < \epsilon < \infty$

- ▶ Then:
$$\Pr(y_{ij} = 1) = \frac{\exp(\vec{z}_{ij}'\vec{\alpha})}{\sum_{k=1}^J \exp(\vec{z}_{ik}'\vec{\alpha})}$$
 - ▶ Likelihood:
$$L_i(\alpha) = \frac{\sum_{k=1}^J y_{ik} \exp(\vec{z}_{ik}'\vec{\alpha})}{\sum_{k=1}^J \exp(\vec{z}_{ik}'\vec{\alpha})}$$
 - ▶ Log-Likelihood:
$$\log L(\alpha) = \sum_{i=1}^n \ln L_i(\alpha)$$

Alternative-Specific Conditional Logit Model (CLM)

▶ **STATA** `asclogit y FSD FSA EFF MM,`
Command: `case(i) alternatives(j) noconstant`

▶ **STATA**
Results:

```
Iteration 0: log likelihood = -317.10088
Iteration 1: log likelihood = -308.55197
Iteration 2: log likelihood = -308.51212
Iteration 3: log likelihood = -308.51212

Alternative-specific conditional logit
Case variable: i
Alternative variable: t
Number of obs      =          990
Number of cases    =          330
Alts per case: min =           3
                  avg =          3.0
                  max =           3

Wald chi2(4)      =          80.96
Prob > chi2       =          0.0000

Log likelihood = -308.51212
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
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Alternative-

- ▶ STATA Command
- ▶ STATA Results:

Excluded SELF because of multicollinearity

Efficiency Even More Important! ($z = 2.63$)

```
Iteration 0: log likelihood = -317.10088
Iteration 1: log likelihood = -308.55197
Iteration 2: log likelihood = -308.51212
Iteration 3: log likelihood = -308.51212
```

```
Alternative-specific conditional logit
Case variable: i
Alternative variable: t
Number of obs      =          990
Number of cases    =          330
Alts per case: min =           3
                  avg =          3.0
                  max =           3
Wald chi2(4)      =          80.96
Prob > chi2       =          0.0000
```

Both Inequality Aversions Matter! ($z = 2.32/2.04$)

```
Log likelihood = -308.51212
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
t						
	FSD	.3267221	.1405881	2.32	0.020	.0511745 .6022697
	FSA	.3447768	.1688655	2.04	0.041	.0138065 .6757472
	EFF	.1879009	.0714842	2.63	0.009	.0477943 .3280074
	MM	.0804075	.0895162	0.90	0.369	-.0950409 .255856

Observed Heterogeneity in CLM

- ▶ Add **Interactions** in CLM to
 - ▶ Explain subject differences with subject characteristics
 - ▶ $male_i = 1$ if male; $= 0$ if female

$$U_{ij} = \alpha_1 FSD_{ij} + \alpha_2 \underline{FSD_{ij}} \times male_i \\ + \alpha_3 FSA_{ij} + \alpha_4 \underline{FSA_{ij}} \times male_i \\ + \alpha_5 EFF_{ij} + \alpha_6 MM_{ij} + \epsilon_{ij}$$

- ▶ **STATA Command:**

```
asclogit y FSD male_FSD FSA male_FSA EFF MM,  
case( i) alternatives(j) noconstant
```


Observed Heterogeneity in CLM

▶ STATA Results:

```
Alternative-specific conditional logit
Case variable: i
Alternative variable: j
Number of obs = 990
Number of cases = 330
Alts per case: min = 3
                  avg = 3.0
                  max = 3
```

```
Log likelihood = -299.6794
Wald chi2(4) = 85.42
Prob > chi2 = 0.0000
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
FSD	.1907648	.1552983	1.23	0.219	-.1136143 .495144
male_FSD	.2535549	.1281861	1.98	0.048	.0023147 .504795
FSA	.5649655	.1879811	3.01	0.003	.1965293 .9334017
male_FSA	-.5760542	.192775	-2.99	0.003	-.9538863 -.1982221
EFF	.1606768	.0741216	2.17	0.030	.0154012 .3059525
MM	.1170375	.091562	1.28	0.201	-.0624207 .2964958

Male exhibit more Envy ($z = 1.98$)

Female exhibit more Guilt ($z = -2.99$)

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